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A Novelty Approach to Retina Diagnosing Using Biometric Techniques With SVM and Clustering Algorithms

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ABSTRACT A method to extract the retina characteristic points for the purpose of medical diagnosis of the human eye is presented in this research. The proposed method helps to make the primary decision about the illness faster and can be used on mobile devices. The algorithm is mostly based on the characteristic points (the so-called minutiae). These structures are commonly used in the biometric applications for fingerprint-based people recognition. In the case of the conducted research, this trait was used to differentiate healthy eyes from unhealthy ones. The methods were evaluated by appropriately implemented algorithms, showing promising results. Each solution was created with object-oriented programming language. The accuracy of the classification (healthy versus samples with pathological changes) was evaluated using four algorithms: *k*-Nearest Neighbors, *k*-Means and Support Vector Machines (SVM) with linear and third-degree polynomial as well as our own approach based on counting the minutiae number. Performance requirements were also checked, and it was verified that the computing power of modern mobile devices is sufficient to implement the proposed solution. The highest accuracy result was equal to 96,45% and was obtained with the third-degree polynomial SVM. This was a novel approach. For comparative purposes, we also implemented currently used solutions for image analysis – deep learning (DL) and Convolution Neural Networks (CNNs). Both medical and computer science backgrounds are presented in the work with the main methodology components to include image segmentation using the Gaussian Matched Filter, binarization by Local Entropy Thresholding and classification with the previously mentioned approaches.

INDEX TERMS Biometrics, clustering algorithms, retina disease diagnosis, security, support vector machines (SVM).

I. INTRODUCTION

Globally, around 2.2 billion people live with some kind of vision impairment [1]. A number of such impairments are connected with pathological changes that do not allow people to see properly. In the literature, we can find multiple diversified types of such changes. The change in which the retina peels away from the underlying layer is called retinal detachment. About 1 in 10.000 of the population will suffer a retinal detachment [2]. When it occurs, the patient notices a curtain-like shadow over the visual field. Progression can be rapid when a superior detachment is present [3]. Retinal vein occlusion is a common vascular disorder of the retina. It is a blood flow blockage that usually manifests as dilatation and tortuosity of the affected veins with retinal hemorrhages. The patient complains of a sudden painless blurred vision [4]. However, the early stage of such diseases may not be noticed by the patient and even by an ophthalmologist.

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In such situations, diagnostic methods based on computer techniques may be helpful, although they should not require high computing power. It is connected with the fact that there should be a possibility to use these solutions in basic medical care and even during self-monitoring with mobile devices – e.g. smartphones. To achieve this, algorithms used in such a solution should consist of fast and robust steps. Moreover, each of them should not require advanced resources, such as latest computer graphics cards. Each part of the solution should be realized with smartphone computing power (we do not consider usage of cloud computing because retina images are sensitive data in the terms of law). We should also remember that resources of smart devices are strictly limited.

The retina image is one of the most common traits used to identify and verify people. The biometric techniques allow obtaining high accuracy level in the case of people identity recognition. Due to these statements, the authors decided to use these techniques for illness identification.

Biometrics [5], [6] help checking the true identity of a person. It is the technical term for human personal data verification or identification. People's identity recognition is performed through the measurement of behavioral, physiological or hybrid (for instance voice) characteristics of a person. Making a direct connection between biometrics and biometry is a frequent misconception. They are both connected with biology. However, biometrics deal with human identity recognition (and it has origins in computer science) whilst biometry deals with the statistical methods of biological tissue measurements and it is mostly associated with medicine. Several biometric techniques for human identification and authentication have been proposed [7]–[11]: fingerprint, hand geometry, palm print, face, iris, retina, ear and eye movements, voice, signature, body odor etc. There are no two identical retinas and even the right and left eye of one person are not the same. For this reason, we use retinal blood vessels for personal identification as the most precise means, besides DNA. The retina is a complex ocular structure composed of many layers. A place on the retina where the optic nerve exits the eye is called optic disk. It is the entry point for the major blood vessels. That fact helps localize the main structure of the retina in human identification but also allows the assessment of eye health.

If we take a look at the retina from the medical point of view, it can be concluded that there are pathologies that may hide or change the retinal vessels. For this reason, the authors decided to adopt approaches known in biometrics to develop methods of determining whether the analyzed image represents a healthy eye or one with pathological changes. We examined patients with common eye diseases, which usually decrease the visual acuity. However, the early stage of some retinal disorders may not be noticed by patients [12]. This fact explains why routine eye examination such as retina photo is helpful. Recently, considerable attention has been paid to prevent rather than treat diseases.

Working out a method based on human identification techniques using retina pattern for disease differentiation and their early detection is the aim of this study. The main goal of this research was to prepare methods that can be used in self-monitoring solutions used with smartphones or deployed in embedded systems. We have to once again state that such devices do not have high computing power. This is why we have to carefully select proper algorithms that can be implemented in them.

In this paper, we prepared an algorithm for retina classification on low computation power devices (that can be used in basic medical care and self-monitoring) as healthy or with pathological changes and considered two approaches for this aim. The first one is image processing-based and classifies retina based on the number of the detected minutiae whilst the second one uses Support Vector Machines (SVM) – linear and third-degree polynomial. During the experiments, we took into consideration two eye diseases: retinal vein occlusion and retinal detachment. Little research has been done in this field in the world so far, as will be discussed in this work. We also have to state that in most approaches related to retina diagnosis deep learning methods currently described in the literature are used. In fact, this is the main cause why these solutions cannot be used on the devices with low resources (deep learning algorithms require high computing power).

II. METHODS

A. PARTICIPANTS

A base of 500 processed retinal eye images of patients from our Clinical Hospital of Medical University of Białystok (MUB) and publicly available DRIVE, STARE and Kaggle Retinopathy databases were included in this study. The database used in further experiments consists of 250 healthy samples and 250 images with pathological changes except for the experiment using deep learning methods, in which the above-mentioned numbers of images are too small to obtain precise results.

All methods were carried out under the relevant guidelines and regulations. All experimental protocols were approved by the Bioethical Committee of our University. Informed consent was taken from participants qualified into this prospective study. Participants who were selected to undergo the examination were asked to fill in and complete questionnaires.

Participants were divided into 4 groups:

1. Healthy patients with the normal, primary retina.
2. Retinal vein occlusion.
3. Advanced retinal detachment, which hides the main retinal vessels.
4. Peripheral retinal detachment.

The duration of the study was 2 years. Control periods were appointed from 7 days to 2 years, depending on the disease dynamics. Each eye examination contained a visual acuity test, slit-lamp examination, intraocular pressure measurement, fundus examination using volk lens and fundus camera, and in some glaucoma cases – gonioscopy.

Eye image registration by taking photos helped follow the progression of the lesions in the retina. Cooperation between authors within pathological changes detection in retina color images was documented in the form of research papers [7], [12], [13]. From the technical point of view, image processing comprised preprocessing, mask creation, vessel segmentation, binarization, thinning and minutiae extraction. The number of detected minutiae was used as the confirmation of the presence of eye disorder and likely disease recognition. The next step involved the attempt of differentiation between disease types. Moreover, the authors also have tried more sophisticated approaches for automatic classification whether the examined eye is healthy or not. The results obtained during experiments are presented in section 3.

B. PROPOSED METHODOLOGY FOR RETINA IMAGE PROCESSING AND RECOGNITION

The main idea of the proposed image processing method is to extract the characteristic points on retina images. The landmarks of retinal vessels are bifurcations, crossings and endpoints. These elements are called minutiae and are commonly used for fingerprint based-identity recognition [14]–[16]. During the state-of-the-art analysis, we did not find any approaches to retina diagnosis based on minutiae counting. General parts of retinal image processing within the proposed algorithm are shown in Fig. 1. The image first goes through preprocessing with basic image processing algorithms. Then, an appropriate mask is created to extract retina from the tested image. Next, vessel segmentation and binarization are performed. The fourth step is connected with thinning and skeletonization followed by minutiae extraction. This way, the next step is reached, namely counting the number of minutiae on the resulting image. The last stage of the proposed approach is to classify retina with two types of methods: simple threshold calculation and clustering algorithms.

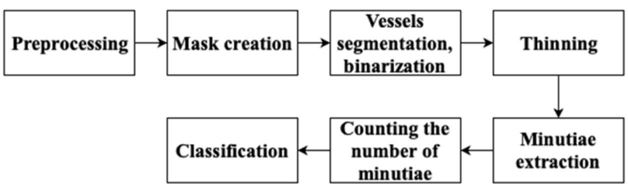


FIGURE 1. Retina image processing and recognition.

Original retina color image is the input to our system and is shown in Fig. 2.

C. PREPROCESSING

The first step of image preprocessing is picture conversion into its greyscale level, denoising, enhancing the contrast and then normalizing the histogram. It is noticed that retinal vessels are best visible on the green color channel [13], [17]–[19]. Because of the nontypical case of the retina images, we applied two methods to convert the image into its grayscale level. The first method uses only green channel and is presented in Fig. 3(a). The second method is based on grayscale computing by the average of red, green and blue channels calculated on definite weights (Fig. 3(b)). As a part of this work, both methods were implemented. Each of them provides interesting results, although authors concentrate on the commonly used green channel method [17]–[19] in the retina processing algorithms. It is connected with the fact that retinal vessels and all significant details are better visible in grayscale images created on the basis of green channel only.

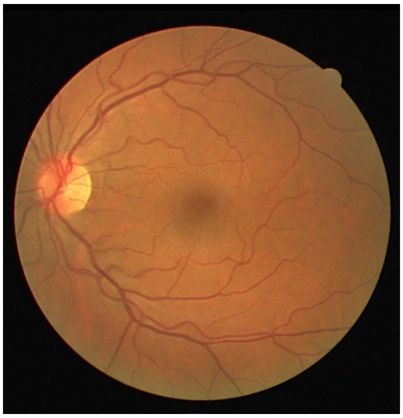


FIGURE 2. Example of an original retina color image used in further processing of the proposed approach.

D. VESSEL SEGMENTATION, BINARIZATION AND THINNING

The next step involves vessel enhancement and segmentation. The simplest solution could be in the form of binarization using one threshold for the whole picture, but unfortunately, this does not usually show good results [20]. In the proposed concept the authors use Gaussian Matched Filter (GMF) method with the binarization by Local Entropy Thresholding [21]. This algorithm allowed the authors to get much more precise results than in the case of one binarization threshold. After this step vessels structure image consisting only of black and white pixels was obtained. Thinning operation can now be applied on the image. It is performed to decrease the width of the vessel to one pixel. Only then it is possible to precisely detect the minutiae. This operation allows to get the clear image of vessels and also decreases the time of image processing.

E. MINUTIAE EXTRACTION

The next step implies minutiae extraction, that is finding bifurcations, crossings and endpoints on vessel distribution. This can be done with the aid of masks as structural elements to avoid detecting false minutiae. The authors used additional process starting from denoising of pre-separated vessels using Hierarchical Growth Algorithm [28] and then removing unconnected vessels. A recursive algorithm is used to move from vessel pixel to the next pixel counting the

(a)

(b)

FIGURE 3. **(a) Retina image after conversion with the green channel (level), (b) average value (grey-scale) of the RGB channels. The most considerable difference between Green and RGB channels is in the brightness of the processed retina. The authors confirmed that the vessels are best visible on the green color channel.**

number of them. Finally, the vessels with length in pixels smaller than specified threshold (experimentally set to 60) are removed from the retina image.

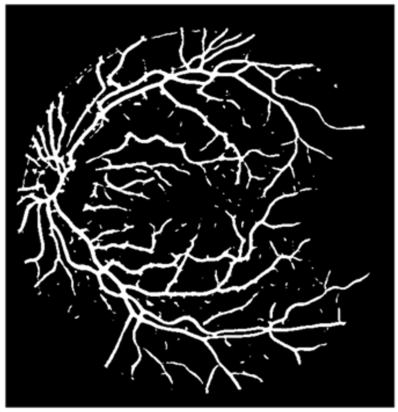
As the last step of image processing, we extract minutiae and then automatically count their number. In this work, the authors used the Crossing Number (CN) algorithm [29] for minutiae detection (Fig. 5). This is a widely used algorithm for this aim. It is based on defining the 8 closest neighbors of each analyzed pixel.

The algorithm flowchart of the complete computer system from image acquiring to minutiae extraction and hence the minutiae counting is presented in Fig. 6.

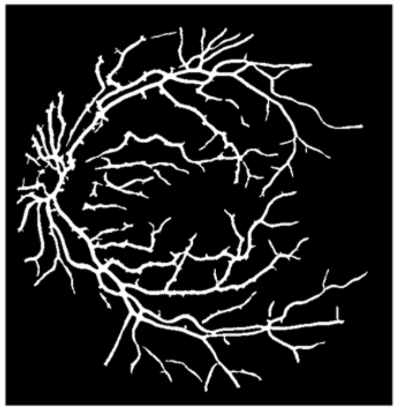
To conclude the authors' methodology, the main premise is that some diseases change the number of detectable minutiae. This makes it possible to determine whether we are dealing with a healthy or diseased eye image and subsequently physician can promptly diagnose the disease.

III. RESULTS

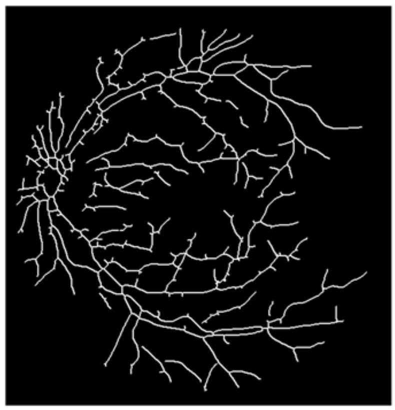
The experiments were divided into five main parts. Three of them were aimed at determining whether the analyzed image shows the healthy sample or retina with pathological changes.



(a)



(b)



(c)

FIGURE 4. **Image vessel segmentation before (a) and after (b) filtering from unnecessary elements. In this case, the authors have used Gaussian Matched Filter [22]–[25] (GMF) with the binarization process done by Local Entropy Thresholding [26]. This algorithm is commonly used in the segmentation step for the diversified medical images. We also used them to detect piecewise linear segments of blood vessels by creating 12 different mask filters and search for vessels every 15 degrees. The authors tested different angles of the mask rotation although 15 degrees provided the best results – most of the vessels were clearly visible. Blood vessels usually have poor local contrast and the known edge detection algorithms have shown unsatisfying results. As can be seen in (b) the picture was cleared from short, disconnected elements. (c) Retina image after thinning by K3M algorithm [27].**

The first investigation was connected with the calculation of the minutiae number thresholds for both groups (and some specific illnesses) whilst the second with usage of Support

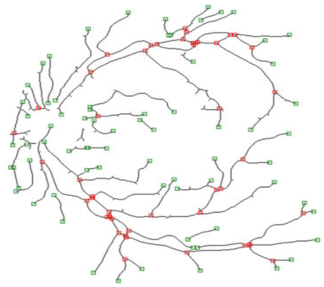


FIGURE 5. **Retina image after extracting the minutiae from its vessels. Circles (red) are the bifurcation points whilst the squares (green) are the starting or ending points.**

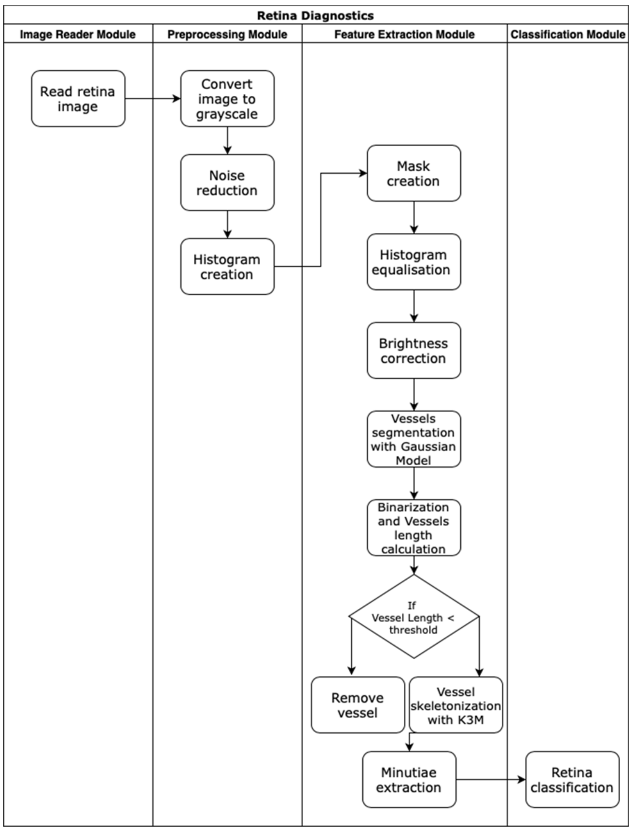


FIGURE 6. **Flowchart of the main functions of the computer program used to generate results.**

Vector Machine and clustering algorithms for this aim. The third part was conducted with deep learning (DL) methods. These approaches were implemented only for comparison with the proposed solutions. These methods are outside the main scope of our experiments, because they require a large number of learning images and much more computing power than what is available in mobile devices and embedded systems. The fourth part involved checking the duration of the processing time and assessing whether the computing power of mobile devices is sufficient to perform all operations in acceptable time. In the last part, we presented computational time results obtained with real devices using Android OS.

A. CLASSIFICATION BASED ON MINUTIAE THRESHOLD

The final result of the picture processing stage is an image with minutiae marked on the blood vessels. In this part of the experiments, we have used the minutiae numbers calculated by our counting algorithm. On the basis of them we established a global threshold by which we decide whether the retina is healthy or not as well as some local threshold for selected specific illnesses. In this case, we analyzed the retina database of 500 samples (consisting of images from well-known databases as STARE or DRIVE, as well as from our own database). Each of them was previously classified by the experienced ophthalmologist. Figure 7 shows examples of the image processing results. In each of the figures the initial retina image and the final effect of processing are shown.

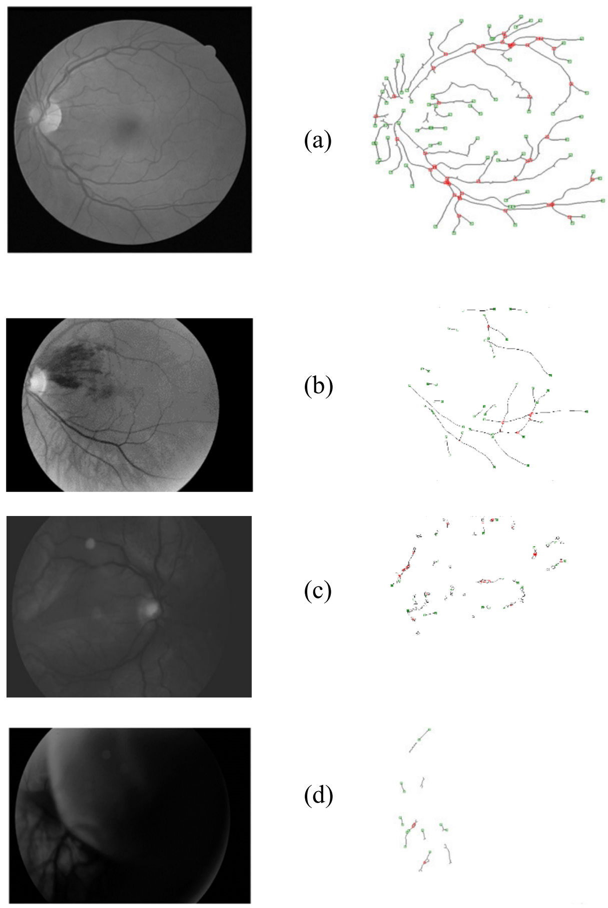


FIGURE 7. **(a) Initial healthy retina image with visible normal retinal vessels (120 detected minutiae). (b) Retinal vein occlusion image with intraretinal hemorrhages (54 detected minutiae). (c) Peripheral retinal detachment image with a small part of the retinal vessels covered (43 detected minutiae). (d) Extensive retinal detachment image which covers most of the retinal vessels (16 detected minutiae) showing an advanced stage of the disease.**

During the conducted experiments we calculated the global threshold for retina classification. Based on high-quality retina images collected with Kova VX-10 fundus camera, we established that more than 72 minutiae always point on healthy retina whereas less than 58 minutiae indicate unhealthy sample. Moreover, we noticed a considerable change in the minutiae number in unhealthy eyes, especially in advanced retinal diseases like retinal detachment (peripheral and extensive). This observation led us to conduct another experiment in which we tried to set local thresholds for various diseases. In this case, we calculated thresholds by which simple, preliminary diagnosis can be performed and as a result disorder type can be stated. Moreover, the authors observed that minutiae number is correlated with the stage of the disease. The results also showed that it is clearly impossible to provide only one number that describes a specific eye disorder. Authors' observations indicated that each disease is represented by a range of minutiae number and that proved to be true for all the considered and studied cases. Table 1 shows the summary of the results.

B. CLASSIFICATION USING SUPPORT VECTOR MACHINES AND CLUSTERING ALGORITHMS

In the second part of the experiments, the authors tried different approaches in the field of clustering algorithms to separate healthy eyes from unhealthy ones. Each image was described by two values: number of ridge endings and ridge bifurcations quantity. Experiments were conducted on the database consisting of 100 training samples (50 healthy and 50 unhealthy eyes) and 400 test samples (200 healthy and unhealthy sample respectively). Example of training set is presented in the form of scatter plot in Fig. 8.

TABLE 1. Summary of the experiments using novel green channel case.

Type of disease	Detected minutiae number
Without pathological changes	>72
Retinal vein occlusion	50-57
Peripheral retinal detachment	41-46
Extensive retinal detachment	<30

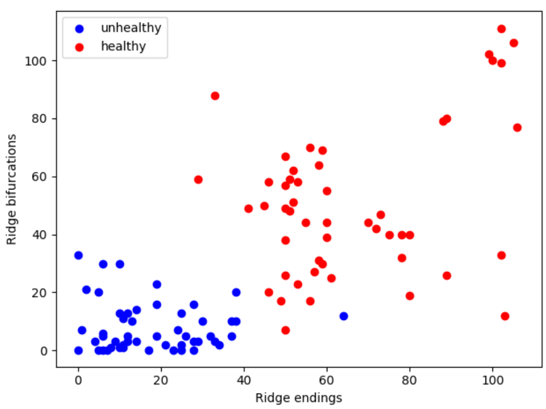


FIGURE 8. Scatter plot of the exemplary training set. The same data were used to create models in all machine learning approaches.

The authors decided to use three popular approaches: Support Vector Machine, k-Nearest Neighbors and k-Means. Execution of each algorithm was repeated 50 times. It is connected with the draw of training samples from the whole database, even though we made sure that training set consisted of 50 healthy and unhealthy samples respectively. During conducted experiments each solution was implemented with Python programming language and Scikit-learn library or with Java and self-implemented frameworks.

The first algorithm's main goal was to divide sample space into two subspaces: healthy and unhealthy. It is done with the parameters calculation of polynomial dividing the scope. During the experiments we used two-dimensional space where each sample was described by the two previously mentioned values. Before testing the method, in the training phase, the SVM classifier was tuned automatically on the basis of GridSearchCV method. This solution is tuning the model by searching for the best hyperparameters (that means a classifier will be claimed as the best when hyperparameters can guarantee the highest recall score). Moreover, we also tried to improve obtained outcomes by usage of diversified kernel types: polynomial, sigmoid and gaussian. However, the most precise results were obtained with 3rd degree polynomial kernel, presented in (1). The results obtained with line and 3rd degree polynomial kernels in SVM method are presented in Fig. 9.

$$K(x, y) = (x^T y + c)^d \tag{1}$$

where x,y are samples from the training set, c is a free parameter that provide information about the influence of higher-order or lower-orders polynomial terms, d is a degree of the polynomial (in our case it is 3), K(x,y) is calculated kernel.

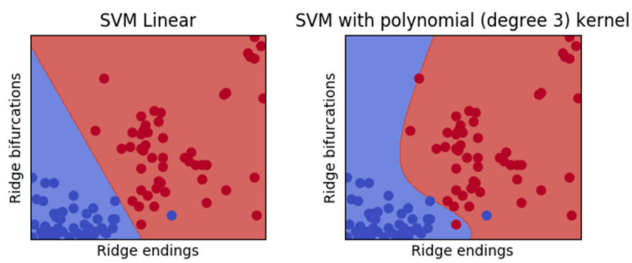


FIGURE 9. Representation of each exemplary training sample in two-dimensional space and polynomial with calculated SVM line.

We have to claim that the results obtained with SVM method are quite optimistic. We observed that automatically tuned hyperparameters in 3rd degree polynomial kernel can guarantee us satisfactory results even when the database consists of 500 samples. We think that this algorithm can also provide good classification rates even with larger databases because during our experiments we observed that the bigger the database the more precise results we can observe.

The second algorithm – k-Nearest Neighbors- is based on similarity calculation between objects. It is done on the basis of the selected metric (in our approach – Euclidean, Manhattan, Chebyshev and Mahalanobis). The next stage is to find k closest samples. The decision about the analyzed object class is determined as the most represented in the set. If two or more classes are equinumerous, then the decision is obtained on the basis of the lowest sum of all distances from each of them. k-Nearest Neighbors testing procedure is presented in Algorithm 1. Moreover, we tested k values from 1 to 50. In Fig. 10. we present accuracy results obtained using this algorithm with different metrics and k parameter values.

The third algorithm, k-Means, is used to calculate two separate sets (in our case: healthy and unhealthy retinas). It is based on similarity measure between each sample and the set center. Table 2 shows the average rates of recognition for different configurations and classifiers. The highest rate in most cases of the studied samples (without Linear SVM and k-Means) was 100%. The authors observed that SVM algorithm is perfect for this kind of data. During experiments, we have also used databases consisting of the diversified number of samples (from 50 to 500). The conclusion is that the more samples are in the database, the higher the accuracy in SVM method we can obtain. Currently, we are working on improving the methodology so that the average accuracy would reach its maximum value.

C. CLASSIFICATION BASED ON DEEP LEARNING METHODS

Although in our work the main goal was to develop methods for retinal images analysis that can be used on mobile devices such as mobile phones (in basic medical care and self-monitoring), we also implemented deep learning methods. This part of the work was created only for comparison with the proposed approaches. In the literature, it was claimed that deep learning-based methods can guarantee high accuracy level in automatic retina diagnosis. We conducted experiments based on algorithms currently used to analyze various images - CNNs [46] to find out what kind of network architecture provides the best results in classification of the healthy versus unhealthy retina images. We provided a dataset from Clinical Hospital of MUB, Department of Ophthalmology. It was our 'goal' dataset. It includes 503 pictures of healthy and 1187 unhealthy retinas (over 3 times more than in two previous experiments). These amounts are significantly smaller than typically used in the CNN network learning process. Used datasets consist of images from different types of diseases, such as: blood vessel thrombosis, effusion, embolus of blood vessel. All of them were labelled by an ophthalmologist (coauthor of this work). Another image database is Kaggle Retinopathy Dataset [47]. It was used to support the goal database in the learning procedures. It consists of thousand images of healthy retina images and samples with retinopathy. This database was initially designed for a competition on detection of the diabetic retinopathy in human eye. These pictures were classified using 5-point scale. Score equal to 0 means that a picture definitely presents a healthy eye, 4 that it is definitely unhealthy. Scores between 1 and 3 are somewhat uncertain. With such vast amount of data (80GB),

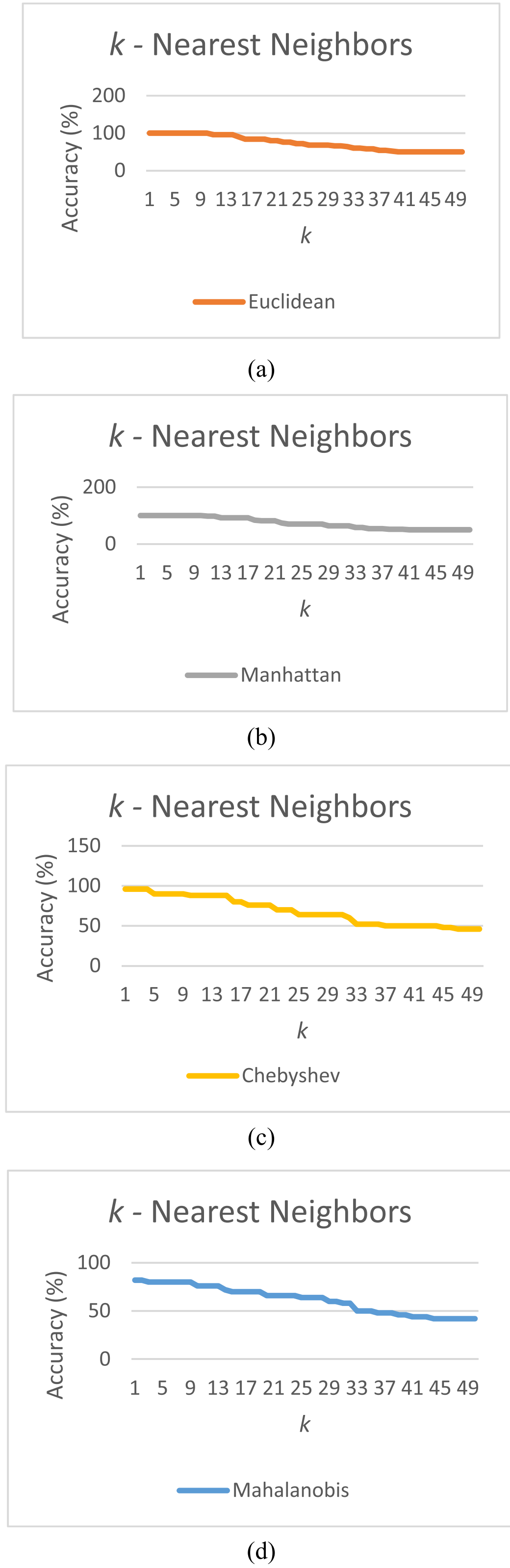


FIGURE 10. Accuracy of k-Means algorithm with diversified similarity metrics: Euclidean (a), Manhattan (b), Chebyshev (c) and Mahalanobis (d).

it was decided to filter the images based on the scores. Desirable images have score either 0 or 4, so that the model is reinforced with suitable data. We decided to take the number

Algorithm 1 Testing Procedure for k-Means Algorithm

```
k-NN testing: {
  accuracy = 0;
  for each sample in SamplesSet: {
    testingSet = SamplesSet.copy()
    testingSet.remove(sample)
    realClass = sample.getClass()
    List<Distance, Class> distances =
new ArrayList<>()
    for each sampleTest in testingSet:
{
      dist, class = calculateDistance
      (sample, sampleTest)
      distances.add(dist, class)
    }
    distances.sort(Method.MIN)
    obtainedClass =
obtainClass(distances, k)
    if(obtainedClass == realClass) {
      ++accuracy
    }
  }
  accuracy = (accuracy /
SamplesSet.size()) * 100
  return accuracy
}
```

TABLE 2. Average rates of each algorithm classification (healthy/unhealthy retina).

Algorithm	Accuracy
SVM (Linear)	**95,25 %**
SVM (3rd degree polynomial)	**96,45 %**
k-Means	80,42%
k-Nearest Neighbors (Euclidean)	73,96%
k- Nearest Neighbors (Manhattan)	73,16%
k- Nearest Neighbors (Chebyshev)	71,56%
k- Nearest Neighbors (Mahalanobis)	64,40%

of sick images that would correspond 1:1 to healthy images. Final quantity of the images from Kaggle dataset was 1503 of healthy and 1503 of unhealthy images. All samples were preprocessed. This step consists of resizing the images and/or converting them into grayscale. As a result, our inputs have the size of 224 × 224 or 448 × 448. In order to enhance our dataset, data augmentation was also used. This operation increases the data set quantity without increasing noise. In our work it was extremely useful when teaching set was very small. In this project all training and validation data was flipped vertically, horizontally and randomly rotated in range from 0° to 45°. Our first implementation used ResNet50 pretrained for diabetes retinopathy detection. We leave weights, biases and the rest of the architecture unchanged, so deep layers holding detailed features are preserved and can be used to classify new 'objects'. As a result, we 'transfer' the knowledge from another model ResNet50 with weights learnt on ImageNet dataset to our target task where we had less images to work with. After trials we achieved accuracy of around 70-75%. Our goal data set (from Ophthalmologist Clinic MUB) was fairly small, hence we used transfer learning [48] as a silver lining. Additionally, it was decided to implement the backbone of ResNet50 not trained and without classification layer and add our own classification layer which consists of 2 batch normalization and 3 dense layers. The 1st dense layer had 512 neuron connections which were activated by Relu function, 2nd dense layer had 256 neurons with the same Relu activation function and final 3rd dense layer which had only two neurons – it is equal to the number of classes in our dataset (either unhealthy or healthy) and was activated by SoftMax function. Once we adopted architecture to our needs, we trained it on Kaggle Retinopathy dataset. We saved pretrained model, then we froze the backbone network and left out only classification layer. We trained classification layer on our dataset (from Ophthalmologist Clinic of MUB), as there are less connections to evaluate. In such a small dataset as ours it was sufficient to achieve satisfactory results. In the end we used backbone architecture of ResNet50 and our own classification layer pretrained on Kaggle Dataset and later trained on Ophthalmologist Dataset As the amount of teaching dataset was fairly small, we decided to introduce optimization element in the network architecture. We tested 3 different optimizers: Adam Gradient, Adam Delta and Adam. Testing set consists of 500 photos ill/healthy (each group was represented by equal number of samples) and comes from Department of Ophthalmology MUB. We managed to achieve nearly 86% accuracy on the best run. In order to deeply investigate the performance of the implemented solution, we looked into predictions for the test samples – how certain the model was about its predictions. Our results were satisfactory: the probability that classified image presents healthy sample was maximally equal to 99.65%, the probability that classified image presents ill eye was maximally equal to 99.99%. Summarizing our work on using DL solutions, it should be stated that we operated on a very small training set compared to those typically used for teaching with DL methods (about 1000 in relation to many thousands). We made slight modification in well-known CNN network architectures (to fit them to small training set) and therefore, we have obtained good results but worse than SVM (about 86% vs 96%). This indicates that despite the high potential of DL, with a small number of learning sets and limited computing power, innovative use of modified biometrics methods gives good results in the basic diagnosis of ophthalmic images.

D. MEASURING OF THE COMPUTATION TIME

The fourth experiment was connected with computation time measurement. From the point of view of our research, there were two categories requiring completely different computing equipment. The first one is devices for the DL method, the second one for all other algorithms. Experiments on the use of DL were carried out using a computer equipped with a CPU Ryzen 7, 2.7 GHz, 16G RAM, with GPU RTX 2070. The most important element was a GPU with 288 Tensor cores and 36 RT cores. Teaching time (without preprocessing) was over 8 hours. The exact time of conducting the classification for one image (using learned network) was not determined, because the equipment with the above-mentioned computing possibilities is not available on mobile devices or embedded systems. In the second category, the equipment needed to perform calculations may have less performance and is in the direct scope of our application purpose. However, before we check how much time was needed on the diversified PC configurations, we calculated algorithm complexity to $O(n^3)$. This value was caused by loops that iterate in the image. The main aim of this experiment was to check whether the proposed solution can be used with satisfactory evaluation time on mobile devices. We do not compare computation time of diversified approaches as it is not in the scope of this work. It was claimed before that the goal of the solution proposed in this paper was to prepare fast and robust algorithm for self-monitoring that can be used in smartphones or embedded systems. By this experiment we simply check whether this goal was achieved or not.

Measures were performed on three different devices. Their configurations are: Intel Pentium IV 1,8 GHz, 256 MB RAM, 40 GB HDD; Intel Core i3 2,4 GHz, 1 GB RAM, 1 TB HDD and Intel Core i9 2,7 GHz, 32 GB RAM, 512 GB SSD. We tried our solution on all of these configurations due to the fact that our algorithm has to run on mobile devices that have much worse components than most of the modern PCs or laptops. The summary of this experiment is presented in Table number 3.

TABLE 3. Summary of the third experiment conencted with time needed for our algorithm on the used devices.

Configuration	Production year	Measured time
Intel Pentium IV 1,8 GHz, 256 MB RAM, 40 GB HDD	2002	1 minute 45 seconds
Intel Core i3 2,4 GHz, 1 GB RAM, 1 TB HDD	2011	1 minute
Intel Core i9 2,7 GHz, 32 GB RAM, 512 GB SSD	2019	25 seconds

According to the results obtained from this experiment, older PCs without powerful CPUs or better operational memory can also be used to achieve the same goal. This leads to the conclusion that mobile devices can definitely be sufficient. This fact, along with the short (less than a minute) processing time, encouraged us to use the proposed solution on modern mobile devices with promising results.

E. COMPUTATION TIME ON MOBILE DEVICES

The last experiment that was carried out during testing phase of our algorithm was connected with calculation of computational time on real mobile devices. In this case, we implemented our solution (we selected version based on minutiae threshold) with Android Studio and uploaded it into four real devices: Samsung Galaxy S20 Ultra (CPU Exynos 990, 12GB RAM, 128GB), Huawei P40 Pro (CPU HiSilicon Kirin 550 5G, 8GB RAM, 256GB), Xiaomi Redmi Note 8 Pro (CPU MediaTek Helio G90T, 6GB RAM, 64GB) and Xiaomi Mi Note 10 (CPU Qualcomm Snapdragon 730G, 6GB RAM, 128GB). To properly calculate the time needed for obtaining the final result of whether the eye is healthy or not we used built-in Java System timer. Just before starting the calculations we run selected clock and immediately after finishing all operations we stopped it. In this manner we obtained the time needed for our solution to produce the final result. On each smartphone we calculated it 50 times. The averaged results are presented in Table 4 below. We can claim that on the basis of obtained calculation times, our solution (based on minutiae threshold) is no computationally demanding and can be used on real mobile devices.

TABLE 4. Summary of the fourth experiment connected with computational time on real mobile devices.

Smartphone	Measured time
Samsung Galaxy S20 Ultra	43 seconds
Huawei P40 Pro	58 seconds
Xiaomi Redmi Note 8 Pro	1 minute 5 seconds
Xiaomi Mi Note 10	1 minute 12 seconds

Moreover, we can claim that obtained results (in computational manner) were much more satisfactory (in the case of Samsung Galaxy S20 Ultra and Huawei P40 Pro) than in the case of computer produced in 2011. It means that the proposed algorithm can produce the results in acceptable time even when run on mobile devices.

IV. DISCUSSION

The purpose of this study was to create a method based on biometric techniques using retina pattern for healthy/unhealthy eye classification (basic diagnosis) that can be used on mobile devices for basic medical care and even in self-monitoring. During our research, we additionally conducted comparative analyses using DL methods. The results obtained using DL were satisfactory for a small number of learning images but required much more computing power and effort in preparing learning sets than known biometric methods. Our work on DL confirmed that in CNN networks huge amount of test images are required to achieve accuracy over 90% and have indicated that they cannot currently be used directly on smartphones and embedded systems. For this reason, further considerations related to the use of minutiae threshold and classification SVM with clustering are simply justified. During all experiments we took into consideration eye disorders such as retinal detachment and retinal vein occlusion. One of the novelties in this work lies in the use of strict, well-known biometric image processing techniques for the analysis of patient eye images. Little research has been done in this particular field by medical or computer researchers so far. The available publications present two areas of work in the field of eye image analysis: disease impact verification in biometric identification systems and the use of image processing methods for the detection of ocular diseases. An example of the first area shows a study considering cataract influence on iris recognition [30] that was more about post-operative results and influence on iris pattern [29]. The second area is rather more frequently applied [13], [30]–[36]. However, in this case researchers mostly focus on detecting one particular eye disease. Each of these works uses different techniques in order to detect the retina disease by image analysis. For example, one of them [34] looks at the problem as an issue of detecting the main retina elements (fovea, optic disc and main arcades) in fundus images. Others [35] use soft computing and machine learning methods to detect pathological features in macular and retinal diseases. Similar idea [36] sees the problem algorithmically on the basis of artificial neural networks. However, in the case of AI-based solutions, there is a need for huge image sets (counted in thousands) and high computational power to get precise results. Moreover, not all of the artificial intelligence algorithms can be adapted for mobile devices, especially due to the requirement of high processing capacity (even latest smartphones do not provide components of this class). The authors' algorithm introduced in this paper can get the final result even when using an old computer with low class CPU and small amount of RAM and ROM memories (current mobile devices consist of superior parts). We proved this fact by the results of the conducted experiments.

There are also approaches connected with retina-based human identification. In [37] an interesting algorithm was proposed. However, there is no detailed information in it about the used solutions and how the system would react when the retina contains pathological changes. Another interesting work [38] used machine learning for automated assessment of retinal vasculature in the oxygen induced retinopathy model. In it, the authors introduced an approach to segment and characterize avascular regions. The biggest disadvantage of this work is that the authors only concentrated on retinopathy, yet they did not consider any other illnesses. Another worth-reading paper was [39]. In this approach the authors used their own similarity function for making comparison between samples and Harris algorithm for retinal veins extraction. The authors examined 480 samples and they considered retinas of only healthy eyes. Hence, the comparison between this algorithm and ours would not bring significant and useful information for readers.

Moreover, the new method introduced in this work differs from the other approaches by its simplicity and less complexity in usage. Currently, a mobile phone with a special overlay is sufficient to take a retina photo at high resolution [40]. The sample obtained from such a device is sufficient to proceed with the further image processing and analysis operations. The retina test can be carried out after a simple training. We took advantage of this fact in addition to our algorithms that were successfully used in biometric human identification systems by retina [3]. The work is mainly aimed at assessing if the analyzed image represents a sick eye, and then it was extended to verify whether the retinal disease affects the proper functioning of biometric systems. Our study shows changes in retina pattern of eyes with diseases. Processing methods will always depend on the image preprocessing and it is very difficult to find one golden solution for a particular problem. Authors' image analysis experiments have shown that green level method showed good results for brighter images whilst darker image processing gave better results on the basis of gray-scale approach. Choosing the right mask for image further processing is highly dependent on whether the retina image comes from a sick or healthy eye.

The first purpose of the examinations was the attempt to observe whether the detected minutiae of the retina vascular pattern could provide sufficient information about eye condition. From the medical point of view, several experiments were considered for retinal diseases preliminary diagnosis. In the experiments, the authors considered both healthy retinas and the ones with pathological changes. The first observations have shown that the minutiae number is significantly lower in the case of unhealthy retinas. On the basis of further examinations, the authors observed that the pathological changes affect the retinal vessels view and gave proof that eye diseases had a significant influence on the retina image and hence on the detected minutiae number. The rapid decrease in minutiae number was noticed in advanced retinal diseases such as retinal vein occlusion or retinal detachment.

Our research also showed that it is possible to automatically separate healthy from unhealthy retinas. Three tested approaches, SVM, k-Nearest Neighbors and k-Means, provided satisfactory results. Each new sample is classified based on polynomial, similarity measure and separated sets respectively. All algorithms are lightweight for computation and can be easily implemented in the devices with low resources.

The concept of retina diseases computerization is rarely studied by researchers. The results of this research showed the suggested methodology could promptly distinguish unhealthy eye based on retina images. In the present study, we show that it is possible to indicate diseases such as retinal detachment and vein occlusion based on the number of minutiae loss during human recognition using retina image. The experiments resulted in creating a database of 250 processed pathological and 250 healthy retinal images. The final result of the processing includes the images showing the system of blood vessels with the minutiae marked on them. For comparative purposes, a summary table was given to include the sort of disease versus the number of determined minutiae on it.

Authors believe that deep biometrics methods utilization can make it possible to study other diseases and would ease the work of ophthalmologists. Moreover, the usual computer methods of treatment use a definite methodology for each specific eye disease whilst our approach is general and uses only one tool for all varieties of diseases. The experiments also showed that it is possible to detect the eye disease based only on the detected minutiae number.

A. SIMILAR SOLUTIONS DESCRIBED IN THE LITERATURE

Another significant part of this work was a comparison between the solution proposed by the Authors with other described in the literature. We analyzed several research papers and describe selected five [41]–[45] with similar aim as the one in this work.

The first approach with which we would like to compare our work was presented in [41]. In this research paper, the authors focused on human identification based on retinal vasculatures. In their work, they pointed out one general problem connected with retina-based recognition that is retina veins pattern deformation caused by scale of image and its rotation. The proposed solution uses Scale Invariant Feature Transform and Improved Circular Gabor Filter to solve these difficulties. The algorithm was tested on VARIA database for human identity recognition. The authors claimed their approach presents robustness to diversified rotations and scale changes. In comparison with our work, theirs does not have anything in common with retina illness detection. The solution of this research can be considered for diagnostic systems although the main question is its usefulness because rotation of retina vasculatures cannot have a real influence on diagnostic decision. Hence, said work is really interesting but only in the case of human identity recognition based on healthy retina.

The article Automatic Detection and Distinction of Retinal Vessel Bifurcations and Crossing in Color Fundus Photography'' [42] has more in common with our approach. The Authors proposed an interesting novel algorithm for detection of two minutiae types (bifurcations and crossovers) in retina vasculature images. For this aim, they used Convolutional Neural Networks (CNNs). The main point of their research was to extract those specific points. In the article they claimed their proposed algorithm can be used for blood clot or other disease symptoms localization. In contrary to our approach, this research work [42] does not propose any classification step (healthy/unhealthy retina). Moreover, the authors do not describe any approach for pathological changes detection. Their work is based only on minutiae extraction from retina veins pattern.

Another article describing the use of NN is the publication Retina and Fingerprint based Biometric Identification System [43]. The authors presented a system that uses both fingerprints and retinal images. However, there is a significant difference in relation to our approach. Minute detection has been used to analyze only fingerprint images and Principal Component Analysis (PCA) has been used to extract the retina features, whereas our method uses minutiae to retinal image. The authors of the article [43] utilized the trained ANN network as the next step to determine reliability. Only 40 images were used and all of them were of healthy eyes. Although the publication is concerned with the analysis of

TABLE 5. Summary of the comparison between our approach and analyzed algorithms.

Research article	Main differences with the approach proposed in this work
Meng X. et. al. [41]	• This work presents retina-based human identification, not illnesses detection. • It does not take into consideration any pathological changes. • The accuracy of the approach is calculated only on the database of healthy samples.
Pratt H. et. al. [42]	• They proposed interesting approach to extract two minutiae types, although they took into consideration crossovers which we did not consider. • The authors used Convolutional Neural Network for minutiae extraction. • The authors collected information about minutiae although they did not present any classification step. They just claimed their approach can be used for pathological changes detection although they did not present any evidence.
Borah T. et. al. [43]	• The authors used minutiae extraction only for fingerprints analysis. • For retina image analysis the authors applied Principal Component Analysis without minutiae extraction. • The purpose of this work was identification system (not detection of any illness) and only 40 healthy eye images were studied.
Ortega M. et. al. [44]	• The authors concentrate on the complete verification and identification system and wrote nothing about illness detection and its influence on the identification/verification process. • The feature vector used bifurcations, yet not as the typical minutiae but determined on the tree of vessels that was thought of as creases (ridges or valleys).
Drahanský M [45]	• The author does general overview of the retina and iris detection and authentication. • He does not focus on the impact of the various factors on identification method. • The author describes some retina diseases but does not describe how they affect authentication. • The work shows some general information about iris and retina, devices which can be used to obtain images and nothing about their analysis. • The author's conclusion is that there are no devices for people recognition that use retina image.

retinal images, its results cannot be directly compared to ours, since we analyze the influence of unhealthy eye images on the proper person verification.

In the next work, Retinal Verification Using a Feature Points-Based Biometric Pattern [44], a complete identity verification method based on retina images has been introduced. The feature points such as bifurcations/crossover (minutiae-based) were extracted from the vessel tree and used to check similarity. The authors used a method based on level set extrinsic curvature and got interesting results. However, the main differences lie in the aim of the work. We analyzed both images of healthy and sick eyes searching for identification of illness whilst the work in [44] aims at human identification/verification. For this reason, results cannot be directly compared to ours.

In the article Recognition of Eye Characteristics [45] the author does not focus entirely on machine learning; he describes more general information on diseases and problems related to detection and authentication using retina of the human eye. He describes the biological structure of the retina as well as the iris. He gives 3-4 examples of retina diseases but does not describe how they affect detection; he also gave two examples of devices which he used to obtain images of retina.

Summary of the comparison accomplished in this subsection is presented in Table 5.

V. CONCLUSION

In the published literature we can find a few methods based on biometrics that are connected with retina vessels. However, neither of them differentiates healthy images from unhealthy samples on the basis of biometrics data. Mostly these methods are used for human identity recognition. The novelty of our work lies in applying biometric methods for pathological changes detection in retina color images instead of human recognition. However, it should be claimed that our approach can also be used in typical biometrics algorithms as the pre-recognition stage for classification whether retina is healthy enough to be used in the recognition process. Moreover, the proposed solution can be implemented and used in modern mobile devices. The research work and original good results, obtained on the basis of simple machine learning algorithms as well as threshold-based methods, showed that besides the big role in healthcare we expect our research to improve the security and criminology aspects when deciding on considering the retina biometrics as a way of human identification and recognition. This is going in parallel with the development and wide applications of portable fundus camera.

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